Object Detection in Oceanic Sediments using Quadratic Detectors and Wavelets

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Abstract— Methods for processing parametric broadband sonar returns are presented with the goal of locating buried objects from clutter. A gain correction algorithm based on wavelets is employed to correct for frequency dependent signal losses in multiple frequency bands. Quadratic detectors are designed to filter in time, frequency, and spatial domains simultaneously. These normalized quadratic detectors are shown to successfully isolate regions with similar characteristics by exploiting spectral and temporal features in both horizontal and vertical directions. Several examples are presented using data collected at field trials. One open field test was performed by Naval Research Laboratory (NRL) researchers in the Puget Sound. This data set is shown to contain many non-homogeneous sediment and gas layers. Other data sets were collected by NRL researchers in an experimentally controlled, sand filled test tank located at the Lake Travis facility of the Applied Research Laboratory at the University of Texas at Austin. The latter data set presents some of the difficulties with successfully identifying buried objects in sandy regions.

Keywords— Wavelet, quadratic detector, parametric, broadband sonar.

I. Introduction

THERE has been increasing activity in the ocean drilling and exploration, as well as, the placement of transoceanic internet communication lines. These activities have have spawned a tremendous need to be able to locate existing burial and drilling sites and distinguish buried objects from naturally existing imagery. This paper presents the successful application of a wavelet-based gain correction and quadratic detectors to parametric, broadband sonar data to detect and identify buried objects.

Currently, the majority of methods used to solve the problem of sub-bottom object detection are focused on the reflection magnitude using approaches similar to seismic surveying. Accurate identification in regions containing large amounts of clutter is extremely difficult using these approaches.

New, exciting opportunities now exist because of advancements in receiver and transmitter technology. Parametric, broadband sonar combines the frequency sensitivity of broadband systems with the characteristic narrow beam signal produced by parametric systems. This system proves invaluable in surveying and characterizing the ocean floor. The data collected can be used to describe countless qualities of the surveyed area. These characteristics include porosity of sediment layers, grain size of the sediment layers, bottom contour, natural biological influence (decaying sea shells), and unnatural biological influence (sunken ships or garbage). When analyzing these high-resolution data sets, acoustic impedance layers and transient signals are detected. This parametric broadband acoustic response provides valuable spectral information and temporal resolution that would be lost otherwise [1].

New considerations must be made when using broadband sonar. Traditional narrow-band sonar systems consider signal attenuation to be a function of time and sediment type only. The main complexity of broadband sonar is that attenuation is a function of both frequency and time as well as sediment type. To correct for these signal losses, wavelet analysis is applied to selectively determine gain correction for attenuation in specific frequency bands.

Stacked parametric, broadband sonar signals provide high resolution imagery in time, frequency, and spatial domains. Quadratic filters are created to simultaneously exploit the time, frequency, and spatial characteristics of specified burial regions. These filters are successfully shown to identify areas of similar composition and to discriminate dissimilar regions.

II. Statement of Problem

Two main problems are associated with subbottom object detection using parametric broadband sonar. The first problem is that signal losses due to attenuation and beam spreading vary in time and frequency for a particular sediment. These losses must be corrected before continuing to the detection stage. If these losses are not corrected, then objects buried deeper will not appear the same as objects buried near the surface and therefore will not be detected. Wavelet analysis is employed to aid

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14. ABSTRACT
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15. SUBJECT TERMS
Keywords - Wavelet, quadratic detector, parametric broadband sonar.

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in this correction process. The second problem resides in deciphering real objects from clutter. Filters must be designed to exploit the similarities, if any exist, between regions of similar composition. Work by Kalcic [2] suggests unique spectral characteristics exist for similar regions. Other characteristics to be used exist in the shape and in the resonance patterns of objects. Quadratic detectors are developed to compare similarities in spectral, time, and spatial domains of a known test region to an unknown sample. Levels of correlation are then determined and a threshold is used to remove dissimilar regions from similar ones. This results in the successful identification of objects.

III. Description of Data

Numerous experimental data sets were acquired by Naval Research Laboratory Stennis Space Center (NRLSSC). All data sets contain digitally sampled signal returns from parametric broadband sonar pings along a track line. One data set presented in this paper was obtained from an open sea trial in the Puget Sound. This set contains three objects, mud, silt and methane gas layers, and a large amount of natural clutter. The second data set was collected in a series of experiments performed by NRL researchers in an experimentally controlled test tank located at the Lake Travis facility of the Applied Research Laboratory at the University of Texas at Austin. This set contain 3 objects, 2 of which are buried completely in sand while the remaining object is suspended above the sand in the water column. The surface reflection of sand and the signal attenuation in multiple bands makes this set quite interesting.

The data sets in this paper were collected during field tests of the Tri-Parametric Focusing And Location (TRIFOCAL) project. In the TRIFOCAL system, a NUWC P002-hybrid parametric transducer/conventional receiver was used [3]. The two primary frequencies produced by the transducer were 183 kHz and 238 kHz respectively. Together the two frequencies mixed non-linearly in the water column yielding a 55 kHz difference frequency. This fundamental frequency was transmitted into the sediment and then received by the hybrid transducer/receiver.

The block diagram of how a parametric system works is given in figure 1.

The benefit of the parametric signal is that the lower frequency beam produced has the narrow beamwidth of the higher frequency primaries and negligible sidelobes. The beam produced by the P002-hybrid system has approximately a 1.1 degree angle of spread. This is ideal for sub-bottom object detection. In order to successfully locate and identify objects, pings need to be collected with close proximity to each other and little overlap due to spreading. The narrow-beam characteristics of this system provide the information needed for accurate edge detection of buried objects. In turn, this enables discrimination of different regions based on temporal characteristics.

Figure 2 portrays an unprocessed data set recorded on site in Puget Sound. In this figure, the most significant features of the image are the strong reflections of shells near the surface, the methane gas layer located deeper in the sample, the buried object as well as the two phantom returns resulting from beam splitting.

Figure 2 contains strong reflections from many objects referred to as clutter. In order to identify buried objects successfully, clearly, a time-frequency-varying gain must be applied to compensate for signal losses at increasing depths and frequencies, and filters must be designed to discriminate man-made objects from clutter.

Experimentally controlled tests were collected at the Lake Travis test site. These tests were performed in a $24' \times 10' \times 4'$ deep test tank containing three objects, one suspended in the water column and two buried in sand. Figure 3 depicts the tank with one suspended object, the sand surface, one prominent buried object, one unidentified buried object, and two seemingly invisible hydrophones.

To prevent errors while estimating signal losses, the Lake Travis data set must be cropped to remove the known areas of reverberation as well as the suspended object.

IV. Solution

When analyzing this data, band pass filtering is implemented to study the contributions of different frequency bands in the image. These results suggest that unique spectral signatures exist for regions of differing composition. Previous work performed by Kalcic also supports this phenomenon. This tendency coupled with the notion all frequency bands do not attenuate at the same rate in all mediums creates an ideal situation for using wavelet analysis to correct for losses due to attenuation and spreading. Quadratic filters also possess ideal properties to exploit desired unique spectral signatures of objects.

There is a noteworthy problem concerning the idea of unique spectral signatures. The reflection of a buried object is not solely a function of that object's material composition. The reflection is actually a composite response of all the spectral responses of the many materials in which the object is buried. For example, when a metallic cylinder appears in sand, the reflection is not solely a function of the metal, but of the reflection modified by the sand and water. Quadratic detectors provide a method for removing the background plus noise response not associated

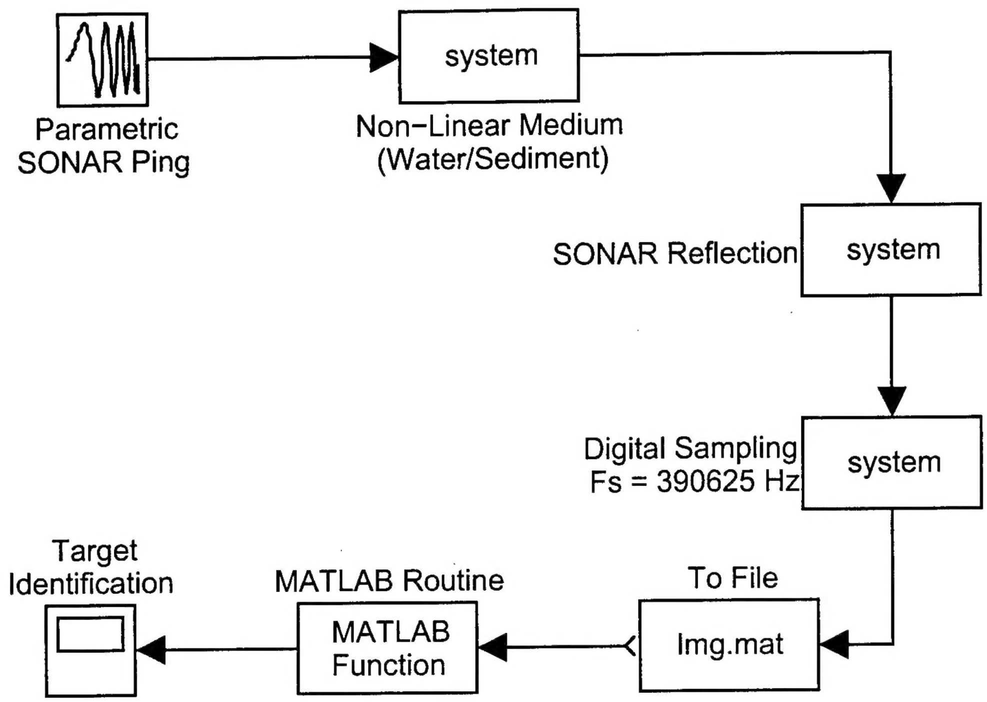

Fig. 1. Block diagram representing the TRIFOCAL P002-hybrid transducer/receiver used in data collection.

uniquely with the desired object plus noise response. This method assumes that regions of object are similar enough to allow for detection.

The procedure for object detection is divided into two sub-sections. The first sub-section is related to gain correction, and the second is to object discrimination.

The general process is shown in the block diagram represented in Figure 4.

A. Gain Correction

The first question to be answered when correcting for losses is whether the losses are stationary. The method discussed here assumes non-stationarity in attenuation, and furthermore assumes that losses may be more accurately represented as a function of time and frequency. A simplistic exponential model for this frequency-varying attenuation is incorporated into the gain correction procedure. This simple model shows great promise, opening the door to more robust attenuation models.

Mathematically the gain correction process can be represented quite compactly using the following equation:

$$y = D'GDx \tag{1}$$

where

x is the raw data column vector representing one ping return,

D is an orthogonal Discrete Wavelet Transform function where $D' = D^{-1}$,

G is a diagonal Time-Frequency gain correction function, and

y is the corrected data column vector representing one corrected ping return.

The frequency range sensitivity of the TRIFOCAL receiver is 30 kHz to 80 kHz. The power spectral density of the raw data does not reflect the same sensitivity levels, meaning system noise must be removed. To remove noise outside the sensitive frequency band, the data is band pass filtered. The sampling frequency of the system is 390.625 kHz, so 80 kHz is well below the critical sampling frequency determined by the Nyquist criterion of 195 kHz. This oversampling permits the data set to be decimated by a factor of 2 without losing any information.

As with all decisions, trade-offs exist when choosing which set of wavelet coefficients to use. Higher order wavelet coefficients provide more frequency resolution, but less temporal resolution. Since temporal characteristics are vital in the detection process, a set of coefficients must be chosen to preserve

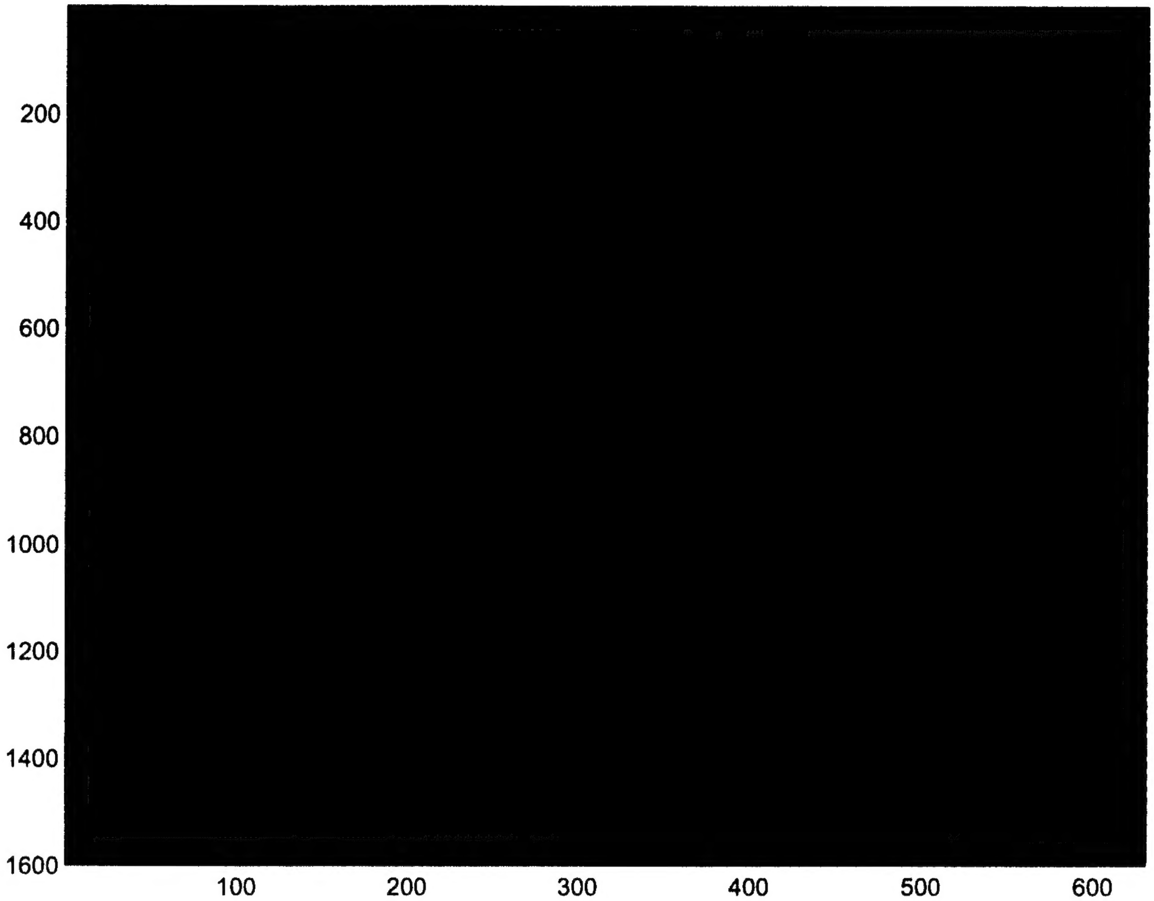

Fig. 2. Non-corrected data set resolving methane gas, buried cable, and shells.

spatial resolution. In this method, the Daubechies-4 wavelet coefficients are selected for their overall robustness and applied to each column of the data set. The 2-D wavelet transform may also be used, but 1-D coefficients are selected for their simplicity in mapping to their appropriate time-frequency locations in the original data ping.

The data is padded with zeros to prevent edge effects commonly associated with wavelet analysis. Correctly mapping wavelet coefficients can be difficult. Padding the original data with zeros to the next length with power of 2 aids in making this task less tedious. Coefficients corresponding to the different frequency bands are then fed into an algorithm which determines the average rate of attenuation for a set of columns. This average over a set of columns prevents the attenuation rates being biased by highly-reflective objects in the sediment column.

Figure 5 shows the first decimation wavelet coefficients which are passed to the attenuation subroutine. These are the coefficients which are mapped to the frequency band ranging between half the new critical sampling rate to the new critical sampling rate (48.8 kHz - 97.7 kHz). objects 1-3 are still easily distinguishable from the other existing imagery. The number of points in this figure is half of the original number of points. As the level of decompositions increases, the spatial resolution and corresponding bandwidth is decimated by an increasing factor of 2.

Figure 6 shows the resulting image after applying this multi-spectral gain correction. This image clearly depicts to what extent the methane layer truly reflects and dominates the image. The three objects are still distinguishable by eye, but the methane layer produces numerous false-positive errors.

Figures 7 and 8 show before and after representations of the Lake Travis data set respectively after cropping out the suspended object and areas of reverberation. The non-gain corrected data set clearly shows one object, but after applying gain correction, two objects and a hydrophone are readily distinguishable by eye.

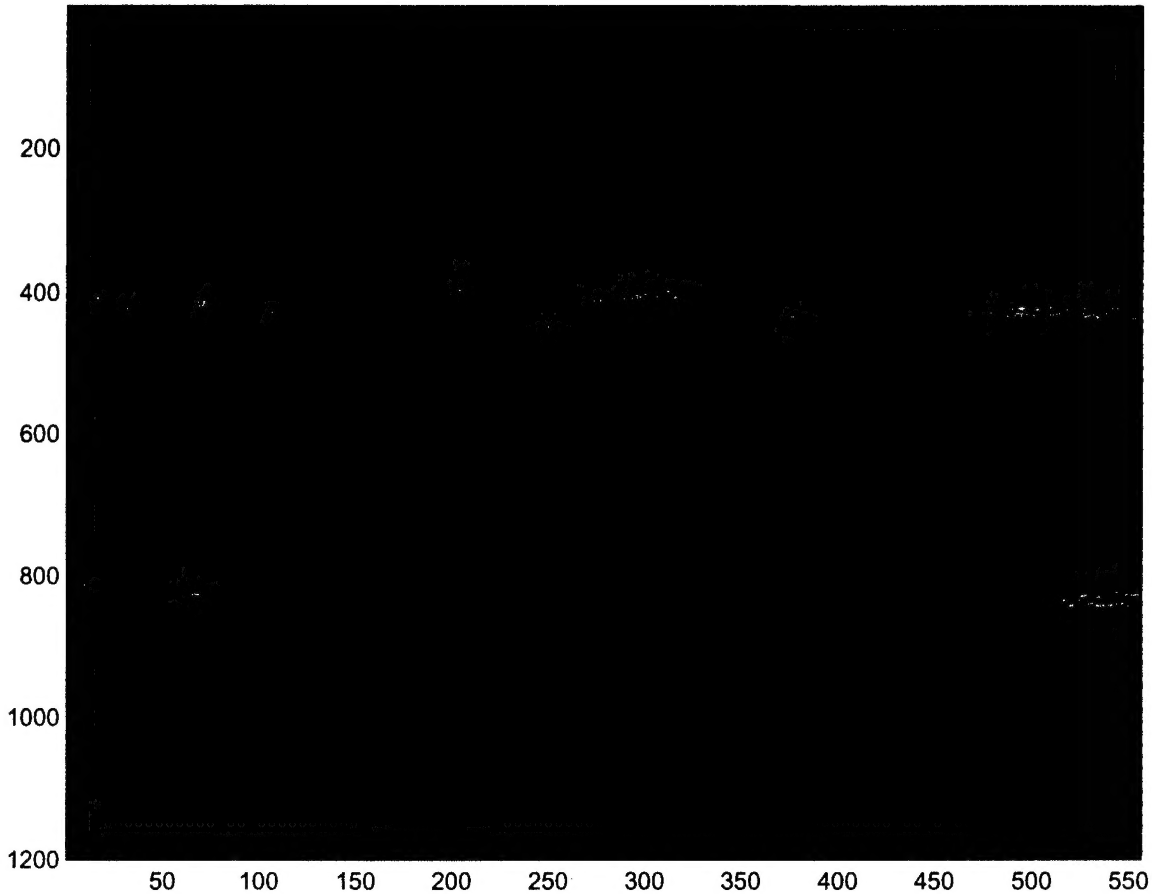

Fig. 3. Non-corrected data set from Lake Travis trial containing one suspended object, two buried objects, and two hydrophones buried in a 4 foot deep test tank filled with sand.

B. Autocorrelation and the Quadratic Detector

The first step in discrimination is to determine the unique characteristics of specific objects. As stated earlier Kalcic shows that unique spectral characteristics exist for each object region using band pass filtering to examine multiple frequency bands [2].

The next step is to determine if regions of similar composition can be identified. Initially, autoregressive models are used to create stationary filters representing each specified region. Results of modeling demonstrate that spectral and temporal differences exist between regions of differing composition. This suggests the use of a quadratic detector as a more rigorous approach.

The autocorrelation of a data stream and its autoregressive (AR) model are roughly inverse analogues between time-variant and time-invariant signals. The AR model may be applied as a whitening filter to the time-invariant signals. Similarly the inverse of the autocorrelation matrix may be applied to the time-varying signal as a whitening filter. The actual relationship is defined in (2).

$$A^2 \approx R^{-1} \tag{2}$$

where

A^2 is the AR whitening filter of a sample column vector, and

R^{-1} is the autocorrelation of the same sample column vector.

Different filters are constructed for each region of specific make-up and tested against each sample column vector using a maximum likelihood ratio. A sample column vector is first whitened with a filter from one of the specified regions and then is subtracted from the same vector whitened by its own autocorrelation filter. Regions similar in composition to the selected test region exhibit a difference near zero. If the region is different in composition than the selected test region, then the difference is larger in magnitude.

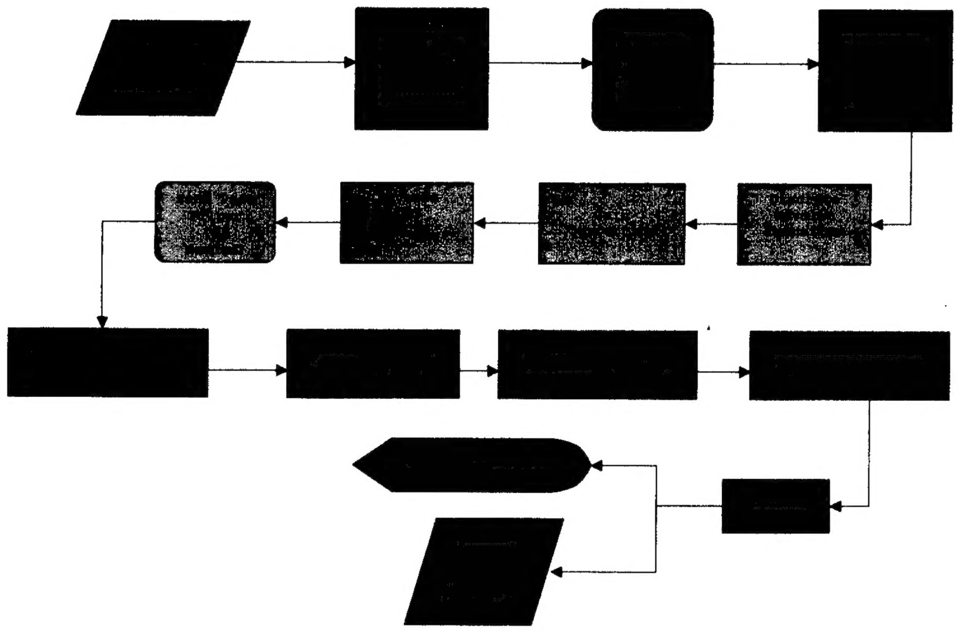

Fig. 4. Block diagram depicting the order of processing.

This hypothesis is represented mathematically in the following equations:

$H_0 : y \sim N(0, R_0)$

$H_1 : y \sim N(0, R_1)$

The quadratic detector test statistic is

$$L(y) = y'(R_0^{-1} - R_1^{-1})y \tag{3}$$

This statistic is tested to threshold, λ.

$H_0 : L(y) \leq \lambda$

$H_1 : L(y) > \lambda$

If H_0 is true, then the two regions are similar in composition. If H_1 is true, then the two regions are not similar.

where

y is a gain corrected data column segment from 1,

R_0 is the autocorrelation of y with unknown composition,

R_1 is the autocorrelation of y with known composition,

$L(y)$ is a quadratic detector, and

λ is a set threshold representing the probability that y_0 is similar to y_1 in composition.

The quadratic filter is essentially a measurement of the power in a signal.

$$y'R^{-1}y = (y'\sqrt{R^{-1}})(\sqrt{R^{-1}}y) \tag{4}$$

where

$\sqrt{R^{-1}}$ is a whitening filter with respect to y.

This filter is applied to the y vector. This process determines the energy in the original vector sample. Then the energy associated with the object is removed from the energy in the sample. Therefore, if the region being tested contains energy well-correlated to the object region, this energy is removed leaving almost no signal in this region. Noting that areas of high correlation have been reduced to low energy and areas of low correlation are still relatively large in magnitude, a logarithmic representation of the new image is used to identify areas of similar composition.

One main inherent difficulty exists in this type of detection that must be corrected. If gain coefficients are changed in the gain correction process, the difference between two regions does not increase by a

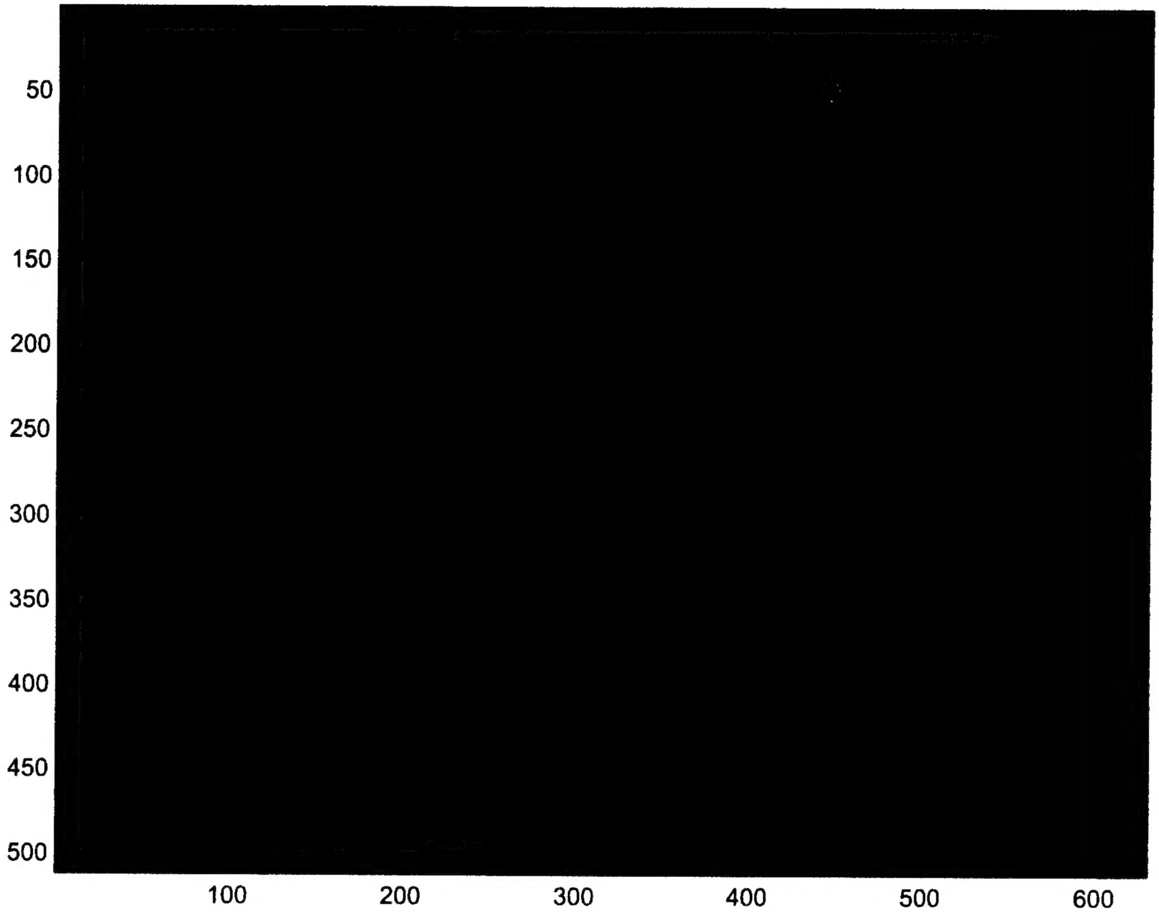

Fig. 5. First decimation coefficients of wavelet transform on Puget Sound Data

multiple of that amount. In truth, the difference between the two statistics is increased by the square of the initial change in gain. To correct for this, the signal energy must be normalized. This is done simply by dividing each statistic by the energy in the original signal:

$$\frac{y'R_y^{-1}y - y'R_{object}^{-1}y}{y'y} \tag{5}$$

A second lesser inherent problem in this technique is related to the measurable differences between background and noise statistics. This technique assumes that one object has the same spectral components as similar objects. This is a problem, as stated before, the reflection is not solely a function of the one material involved. The reflection is a composite of the spectral characteristics of the many materials that surround the object and the object itself. Since each object is suspended in a non-homogeneous mixture of sediments, each measured object signature will differ slightly. If the two object signatures are well correlated, then this process can be employed successfully. This procedure has been shown to work in regions of controlled homogeneity as well as in an open field test with non-homogeneous sediments.

The Lake Travis data set filtered both vertically and horizontally shows high correlation between object areas. Two hydrophones and all objects are clearly distinguishable in Fig. 9 after horizontal filtering only. One phantom object is also readily distinguishable in the image. This object is most likely the result of multipath reverberation. Figure 10 clearly shows the location of both objects after being filtered vertically also. Quadratic filtering of the Puget Sound data not only successfully located all three objects, but also performed excellently in detecting the bottom. Figure 11 is the result of filtering the Puget Sound data horizontally for metallic cylinders. Three objects are clearly distinguishable by eye. A

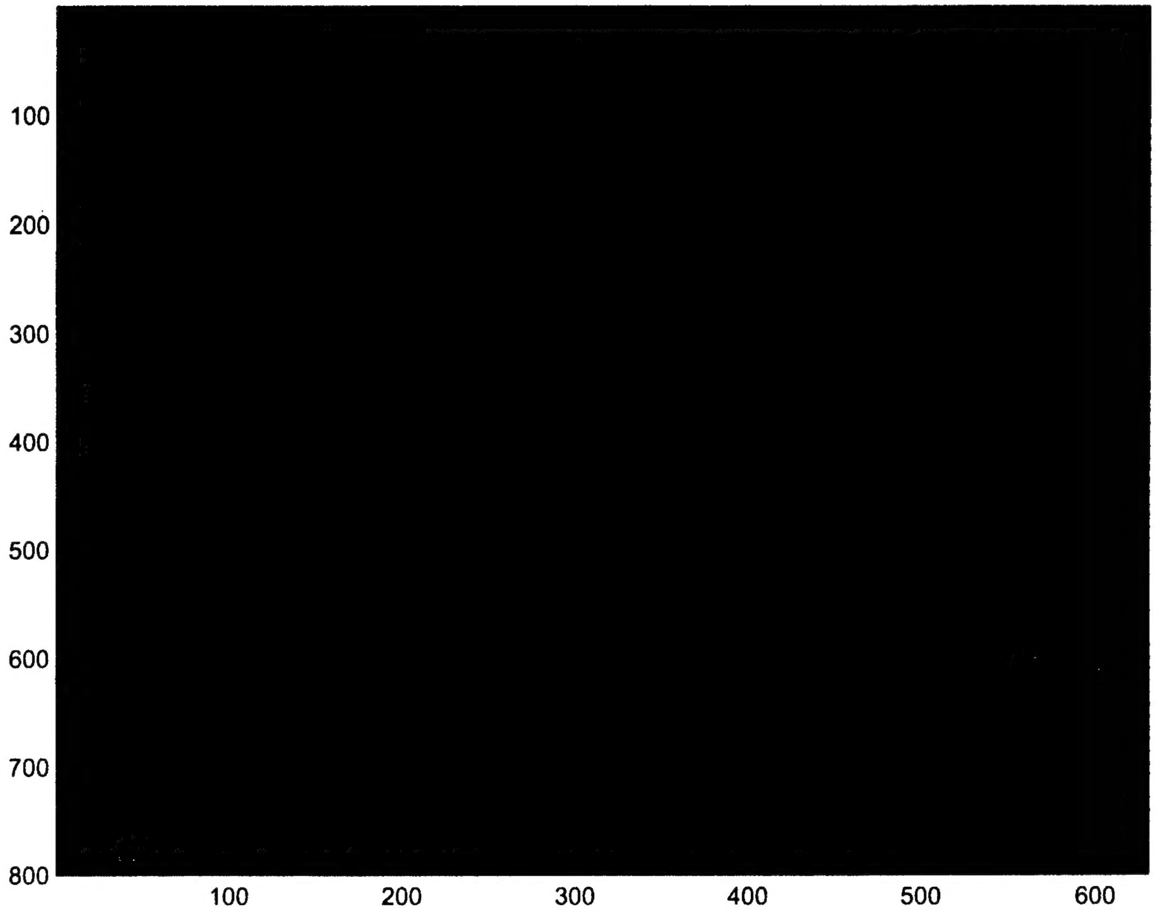

Fig. 6. Gain corrected Puget Sound data set containing most notably three objects and a strong layer of methane.

region of extreme low correlation near the surface of the bottom represents the true surface of the ocean floor. Figure 12 identifies all three object regions after being filtered both horizontally and vertically. Numerous false-positive errors are visible in this figure. In order to remove some of the false-positive errors caused by methane and other natural clutter, longer horizontal samples can be selected so that regions of object significantly differ from regions of methane.

V. Conclusions

In summary, parametric, broadband sonar data contains a wealth of information that can be applied to object detection in oceanic sub-bottom regions. Wavelets aid in correcting for signal losses due to frequency and time-variant attenuation in multiple frequency bands. Quadratic filters and shown to isolate spectral, time, and spatial characteristics of user-specified object regions. This process may be applied to multiple data sets and works in both experimentally controlled conditions and open field tests. Furthermore, quadratic detectors show great promise in bottom detection and contouring.

Future work is planned to heterodyne the raw data to allow for more frequency specific bands as well as to reduce the amount of data being processed. Applying a best-basis wavelet decomposition can be used to accentuate specific frequency bands associated with the specified buried object. More robust models for attenuation can be implemented to enhance gain correction. Overall, this process has shown great results as well as great promise in the field of object detection.

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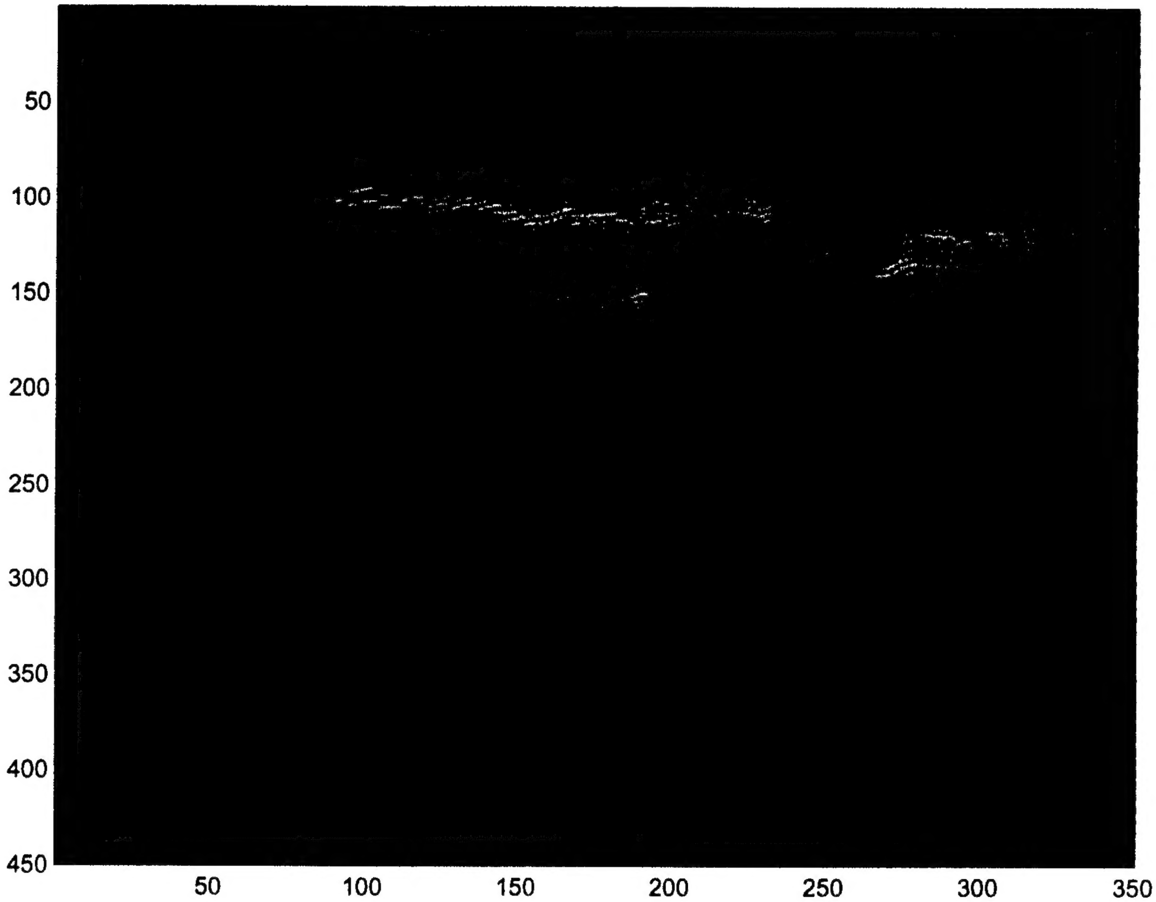

Fig. 7. Non-gain corrected Lake Travis data set containing one prominent object.

search Laboratory. The mention of commercial products or the use of company names does not in any way imply endorsement by the U.S. Navy. Approved for public release; distribution is unlimited. NRL contribution number NRL/PP/7440–00-1007.

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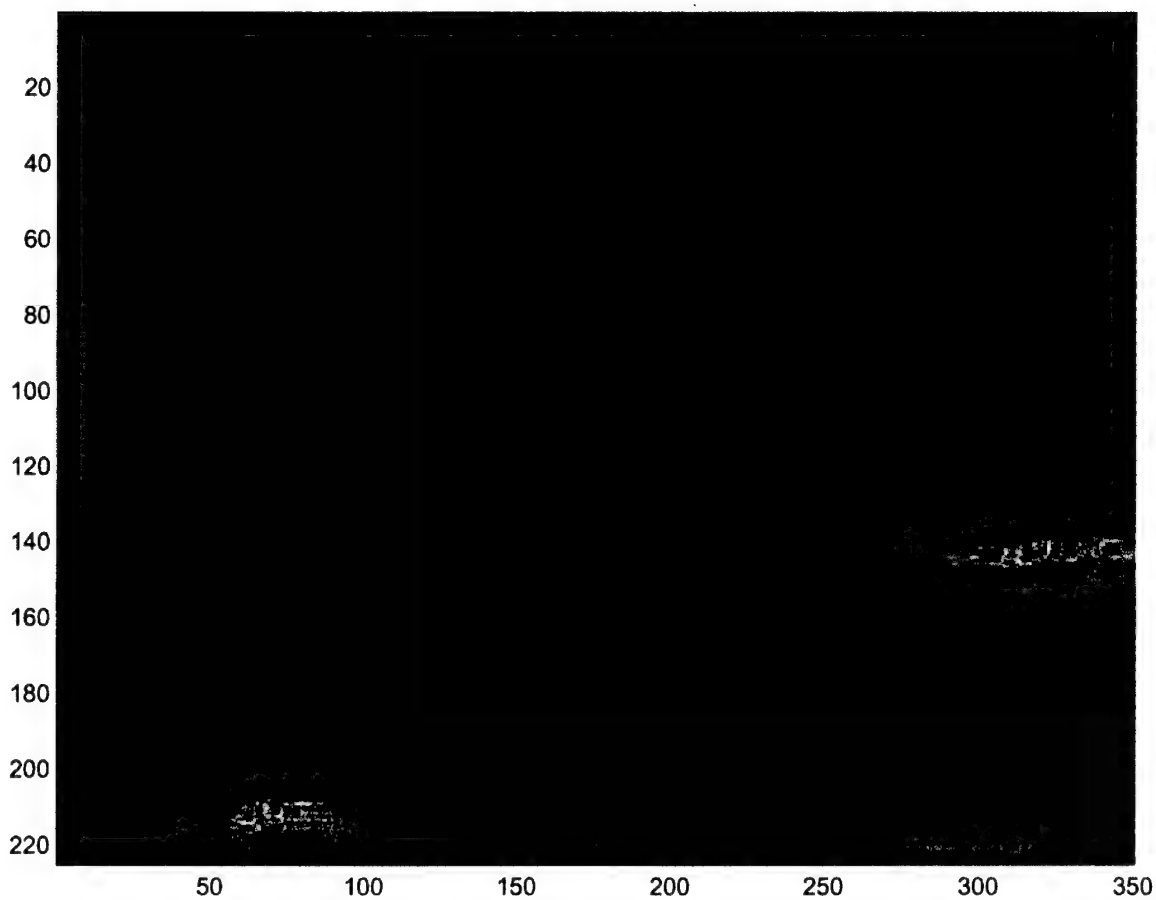

Fig. 8. Gain corrected Lake Travis data set containing most notable two objects and one hydrophone.

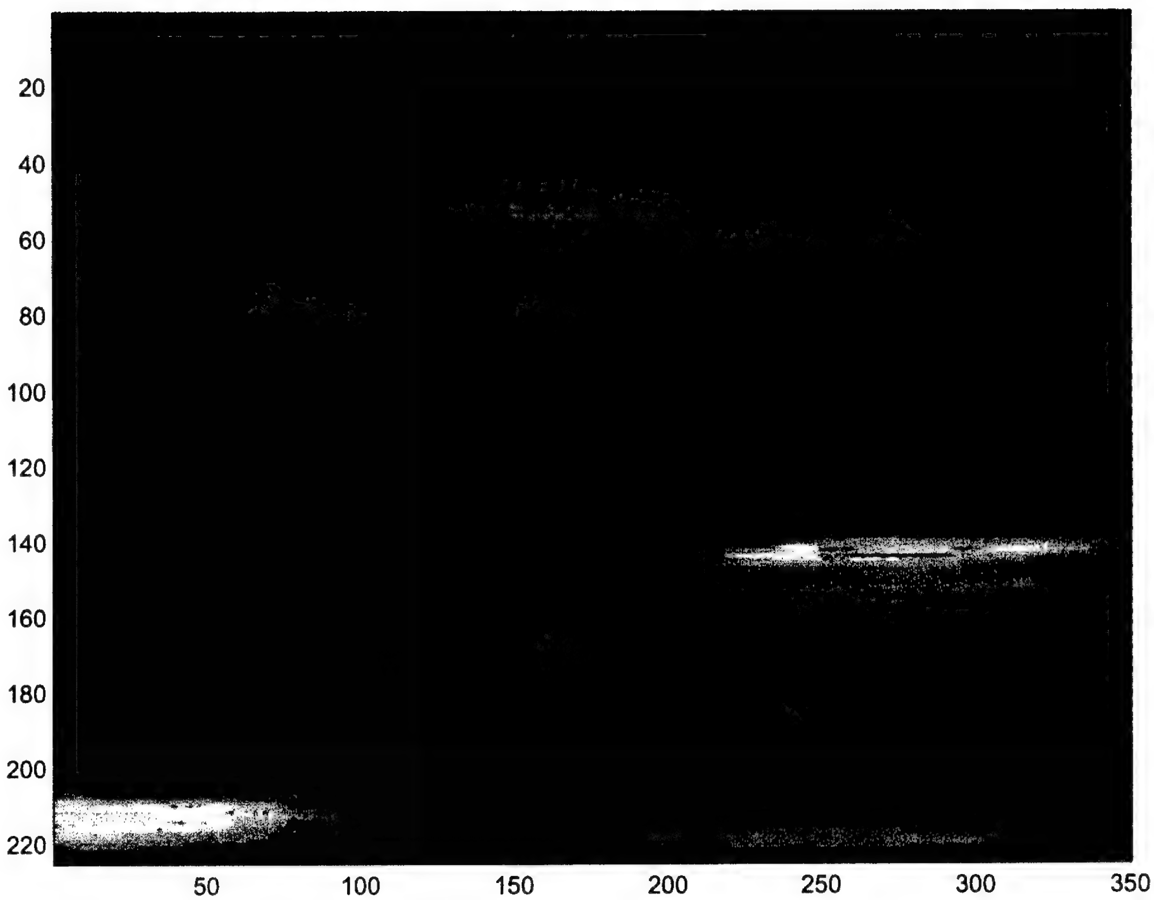

Fig. 9. Horizontally filtered Lake Travis data set clearly indicating locations of two objects, two hydrophones, one phantom object, and a false positive caused by surface reflection.

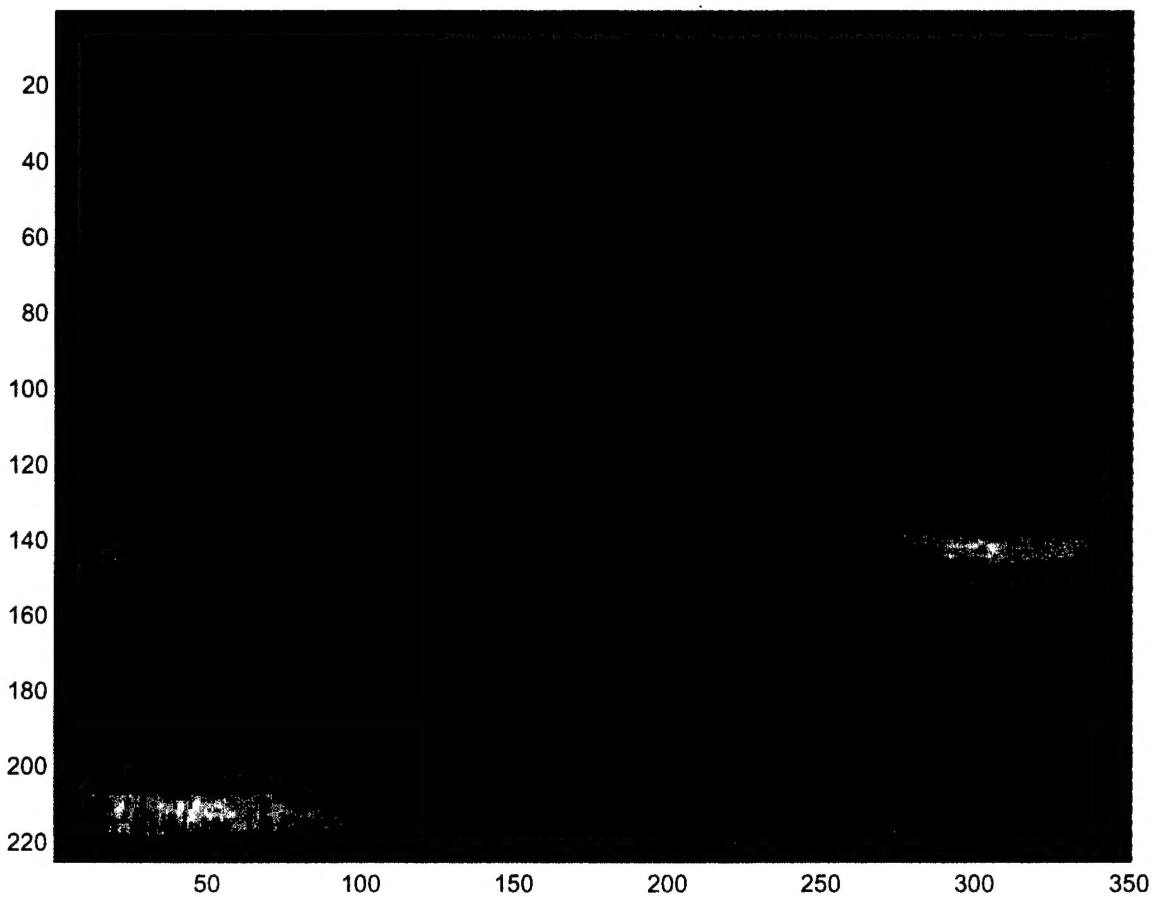

Fig. 10. Vertically and horizontally filtered Lake Travis data set clearly indicating locations of two objects

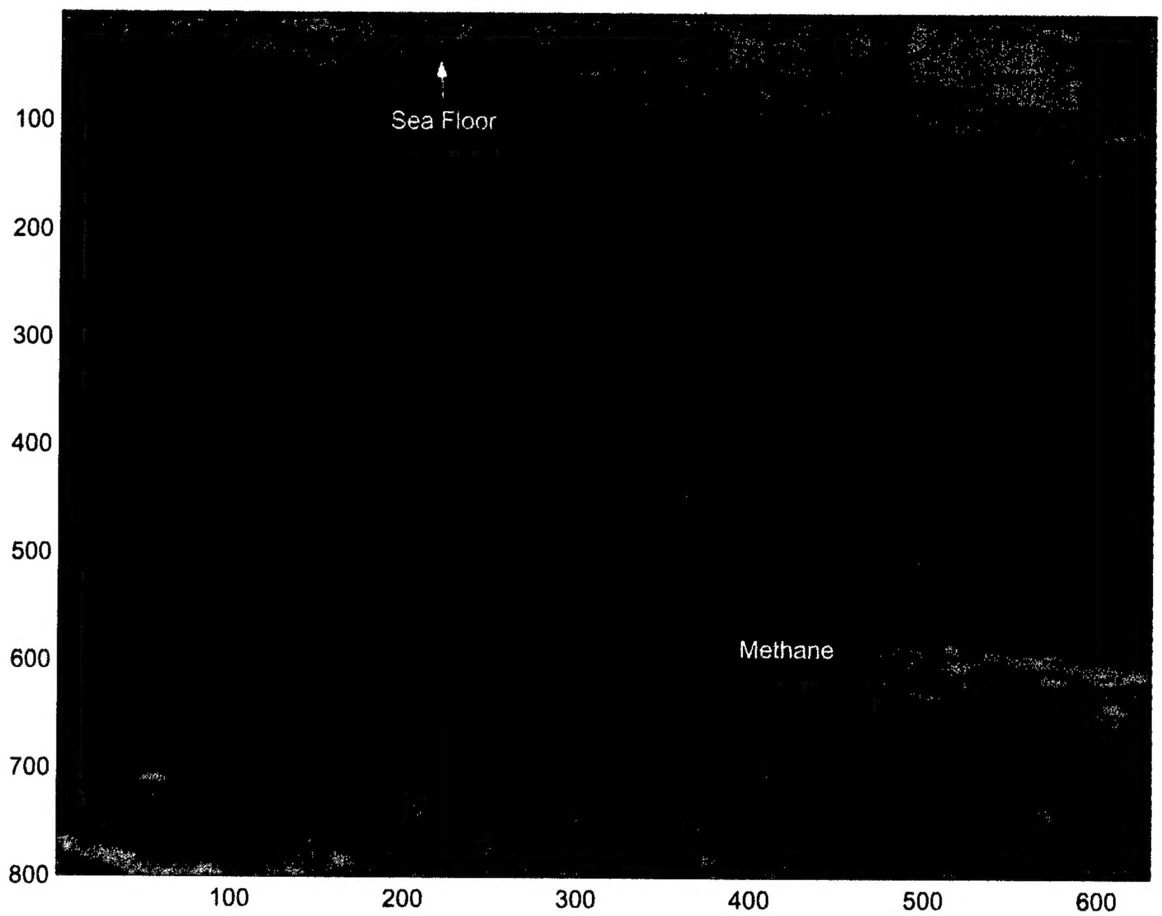

Fig. 11. Horizontally filtered Puget Sound data set clearly indicating locations of three possible objects and true location of the bottom surface.

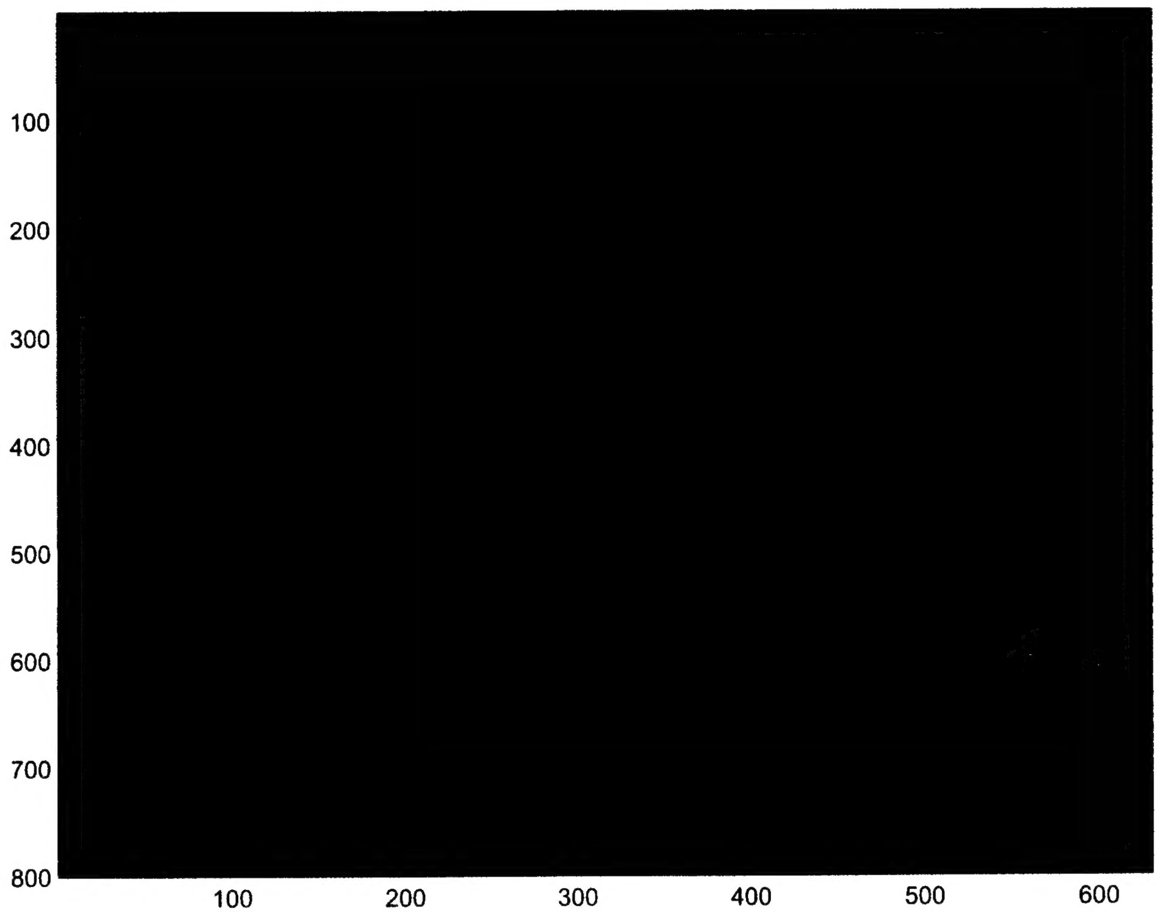

Fig. 12. Vertically and Horizontally filtered Puget Sound data set indicating locations of three possible objects and false-positive locations caused by methane reflections as well as other natural imagery.

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